

Hotel Room Revenue Management: A Systematic Review Using PRISMA Approach

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ABSTRACT

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Revenue management is a critical strategy for hotels to optimize pricing, demand forecasting, and inventory utilization in competitive, data-driven markets. Over time, Hotel Room Revenue Management (HRRM) has gained substantial academic attention. However, existing research often focuses on isolated components such as pricing, forecasting, or overbooking, resulting in a fragmented body of knowledge. This study addresses this gap through a systematic review of HRRM literature from 1980 to 2025 using the PRISMA framework (Preferred Reporting Items for Systematic Reviews and Meta-Analysis). A total of 145 studies were analyzed and classified into three core areas: customer reservation management, inventory allocation, and dynamic pricing. The review also evaluates modelling approaches, solution methods, and the use of real hotel data, while identifying key operational challenges. Findings indicate that most studies emphasize reservation management and dynamic pricing, with comparatively limited focus on inventory allocation. Many studies rely on single-hotel contexts and mid-sized hotels, limiting generalizability and scalability. Inconsistent data usage and the lack of standardized HRRM frameworks remain key issues. This review highlights the need for integrated, data-driven HRRM frameworks that combine artificial intelligence, analytics, and optimization to improve decision-making and overall revenue performance.

1. Introduction

The origin of revenue management (RM) traces back to the airline industry in the 1970s, pioneered by Ken Littlewood of British Airways and Robert Crandall of American Airlines. RM was initially developed to optimize airline seat inventory through dynamic pricing (DP) and allocation strategies [1]. The earliest academic inquiry into RM was in 1963 [2]. Following U.S. airline deregulation, RM evolved to incorporate customer behavior and demand-based pricing, transforming inventory control into a strategic tool for revenue optimization [3].

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Inspired by the airline sector, Marriott introduced RM to the hotel industry in the mid-1980s, with broader adoption emerging in the 1990s [4]. Hotel RM focuses on segmenting customers by price sensitivity and managing room inventory through differential pricing to maximize occupancy and revenue. Traditionally, RM in hotels has relied on human expertise, constrained by market complexity, pricing granularity, and limited responsiveness to rapid market changes.

As competition intensifies and customer expectations rise, optimizing hotel revenue remains a central challenge [5]. Revenue managers in international hotel chains embraced RM practices, while local operators are only beginning to recognize its importance. Hotel RM must reconcile complex variables, customer heterogeneity, diverse room categories, time sensitivity, and market volatility. Pricing strategies must also consider seasonality, events, consumer unpredictability, and ethical concerns around fairness and transparency [6].

In the past decade, the rise of data-driven techniques and decision-support systems has advanced RM through DP, where price is treated as a control variable and demand as a price-dependent process [7]. These systems often require substantial investment, restricting their adoption to larger hotel groups, leaving smaller hotels at a technological disadvantage [8].

The complexity of hotel pricing and distribution has been further exposed by disruptions such as the COVID-19 pandemic, reinforcing the importance of agile and competitive RM strategies [9]. With the increasing influence of online booking platforms and consumer price comparison behavior, mastering DP has become critical for sustained profitability and guest satisfaction [10].

Academic research has increasingly formalized RM into a mathematical framework, enabling precise optimization of pricing and resource allocation. Despite a growing body of research on global hotel chains, studies focusing on locally owned or small-scale hotels remain limited, revealing a significant research gap. Notably, room revenue accounts for approximately 70% of a hotel's total income, making hotel room revenue management (HRRM) a core area of interest [11]. HRRM centers around three interconnected pillars: reservation management, inventory allocation, and dynamic pricing. These elements are vital in managing perishable room inventory and responding to demand fluctuations. The goal is to sell the right product to the right customer, at the right time, and at the right price, to maximize profitability while minimizing resource waste.

While previous research has addressed isolated RM topics, such as pricing algorithms or case-specific forecasting models, there remains a lack of integrated frameworks tailored specifically to HRRM. This fragmentation underscores the need for a systematic consolidation of knowledge to guide both academia and practice. This review paper bridges this gap by conducting a comprehensive systematic review using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analysis) framework. This study provides a systematic review of the literature spanning from 1980 to 2025, with a focus on key problem characteristics and model-based solutions in HRRM. The starting year of 1980 is selected to reflect the emergence of modern RM practices following the deregulation of the airline industry, as well as their subsequent adoption in the hospitality sector during the 1980s. The upper bound of 2025 corresponds to the most recent publications available at the time of data collection, ensuring that the review captures current research trends and methodological advancements.

To ensure the rigor and consistency of the review, explicit inclusion and exclusion criteria were established. Specifically, only peer-reviewed studies directly related to hotel RM, DP, demand modeling, and inventory control were included. Studies outside the hospitality context, lacking methodological transparency, or not providing clear theoretical or practical contributions to RM-related decision-making were excluded. Through this structured screening process, the review ensures the relevance and reliability of the selected literature, providing a solid foundation for subsequent analysis.

2. Previous Review Papers

Prior reviews in the field of RM predominantly focused on theoretical foundations, system development, and broad applications across various industries. McGill and Van Ryzin [12] reviewed 40 years of RM practices in transportation, including forecasting, overbooking, inventory control, and pricing; foundational components shared with hotel RM. Bitran and Caldentey [13] provided a foundational review of DP models in manufacturing and service sectors from 1975-2003. They explored both deterministic and stochastic models, highlighting limitations in closed-form solutions and the growing relevance of game theory in competitive DP.

Anderson and Xie [14] examined RM applications in hospitality over 25 years, covering hotels, restaurants, golf courses, and event spaces. Their study emphasized the significance of consumer behavior and inventory control in enterprise decision-making. Ivanov and Zhechev [15] analysed literature from 2000 to 2010, exploring RM processes, tools, and ethical considerations such as price discrimination. They identified gaps in forecasting systems and called for extending mathematical models from single unit to multi-unit settings, incorporating special events into RM strategies. Den Boer and Zwart [16] and Chen and Chen [17] further expanded DP research by examining multi-product pricing, competition, and limited information environments. They highlighted the scarcity of collaborative DP studies and the need to understand how pricing interacts with inventory over time. Vives *et al.*, [18] categorized hotel RM and price optimization techniques, identifying key variables such as demand elasticity and market segmentation. However, existing reviews rarely integrate time-based dynamics, customer booking behaviors, and inventory considerations into a unified framework.

Klein *et al.*, [19] reviewed 105 studies from 2003–2019, focusing on usability in RM mathematical models, including overbooking, opaque products, flexible offerings, and personalization. While hotel-specific discussions were limited, the study noted a trend toward dynamic offer management, moving beyond basic availability control. Binesh *et al.*, [20] conducted a meta-review of 76 hospitality RM articles from 2013 to 2019, revealing that pricing strategy accounted for 27.8% of the studies. However, consumer behavior theories were largely absent, and predictive models for hotels cooperating with online travel agents (OTAs) were underexplored.

In summary, while the existing literature review papers offer extensive insights into general RM principles, there remains a clear gap in systematic reviews focused specifically on HRRM and its problem-specific modeling approaches. Prior studies often address individual components, such as pricing or overbooking, but lack comprehensive integration of booking behaviors, inventory allocation, and DP within a single framework. Therefore, this paper addresses the gaps by focusing exclusively on HRRM, categorizing 145 studies according to problem types and solution models across three key areas: customer reservation management, inventory control, and dynamic pricing. It further synthesizes key operational challenges in hotel RM, including uncertain arrivals, no-shows, cancellations, multi-day allocation, and OTA integration. Correspondingly, the methodological approaches adopted in the literature can be broadly categorized into three groups: (i) stochastic and probabilistic modeling techniques, (ii) optimization-based frameworks, and (iii) heuristic and metaheuristic algorithms.

To the best of our knowledge, this study is the first systematic review to apply the PRISMA framework to HRRM with such a level of granularity. It contributes to the field by systematically mapping existing knowledge, identifying critical research gaps, and providing actionable insights for both academic researchers and industry practitioners aiming to optimize revenue strategies in

increasingly dynamic and complex hotel environments. Table 1 summarizes the existing review studies in this domain.

Table 1
 Previous Review Papers

Reference	Highlight	Year	Number of Papers Reviewed
McGill and Ryzin [12]	Transportation RM developments in fore casting, overbooking, seat inventory control, and pricing.	1959-1999	190
Bitran and Caldentey [13]	Uses of models in dynamic pricing like multiple-product cases, deterministic models, stochastic models, and single product cases.	1975-2003	84
Anderson and Xie [14]	Application of RM across hotels, restaurants, golf courses, and functional spaces.	1985-2010	56
Ivanov and Zhechev [15]	Processes, concepts, and tools in hotel RM systems; ethical factors from price discrimination.	2000-2010	128
Den <i>et al.</i> , [16]	Historical origins of pricing and demand with an overview of dynamic pricing in operations research and management science.	1898-2014	379
Chen and Chen [17]	New types of dynamic pricing problems like multi-product, competition, and limited demand information issues.	1995-2015	132
Vives <i>et al.</i> , [18]	Main factors of hotel RM and variables affecting the pricing optimization process.	2005-2017	152
Klein <i>et al.</i> , [19]	RM mathematical models addressing capacity control, opaque products, flexible products, personalization, risk-aversion, and overbooking in various industries.	2003-2019	105
Binesh <i>et al.</i> , [20]	RM theories, methods, and positions on pricing strategy, demand modelling, business analysis, and performance evaluation.	2013-2019	76
This Review Paper	Detailed review of popular problems and solution models in customer arrival, prediction, no-show, cancellation, overbooking, inventory control, personalized pricing, competitive pricing, etc.	1980-2025	145

3. PRISMA Framework

In this paper, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology was employed to conduct a systematic review of HRRM literature. The PRISMA framework enhances the transparency, rigor, and reproducibility of systematic reviews in academic research, thereby improving the organization and comprehensibility of the subject matter. By providing a structured and standardized approach, PRISMA facilitates clearer presentation of the research process and findings, making it easier for both researchers and readers to understand the scope, development, and implications of the literature [21]. This method was adopted to ensure a comprehensive and unbiased examination of the existing body of knowledge, offering a high-level synthesis of evidence with reduced influence from subjective interpretations.

3.1 Data Collection

The first phase of the PRISMA method involves the formulation of unambiguous research objectives, which serve as the cornerstone for the entire review. The specific aims of this systematic review encompass the following aspects:

- i. Summarizes and classifies the application of HRRM problems and models/solutions from 1980 to 2025.
- ii. Identification and categorization of reservation management, inventory allocation, and dynamic pricing strategies employed within the HRRM.
- iii. identification of prevailing trends and emerging research domains in the field of HRRM.

To address these research objectives, the development of an exhaustive dictionary of search terms and keywords was performed to facilitate systematic and efficient literature search. In this paper, the authors evaluated these criteria based on the problem characteristics of dynamic pricing, the types of data required, model-based solutions, and application areas. In addition, forecasting, overbooking, demand, and inventory are equally important. The compilation contains terms such as 'dynamic pricing' AND 'revenue management' AND 'hotel' AND 'room pricing', OR 'hotel revenue optimization'. At the same time, keywords such as 'No-show' OR 'overbooking' OR 'hotel booking optimization' OR 'hotel stochastic dynamic demand' forecasting' OR 'hotel room inventory allocation' are also selected. Additionally, search terms include 'room inventory allocation' OR 'random customer arrival' OR 'dynamic pricing' in the database search to ensure that the search focuses on literature related to mathematics and computer science, particularly pattern formulation, rather than research related to the social sciences in hospitality tourism management.

Besides, variants and synonyms are identified to ensure exhaustive search coverage. The pursuit of scholarly articles and industry reports has led to a selection of well-known databases, including IEEE explore, Informs, Google Scholar, Science Direct, Web of Science, Springer, and specialized databases dedicated to the hotel sector (e.g. Hotel, Restaurant and Institutional Education Council, Hotel Tech Report). The literature search was conducted in every quarter of 2025 and was limited to works published between 1st January 1980 to 31st December 2025. As shown in Figure 1, through the application of keywords, a total of 1790 relevant papers were recorded from the search results.

By removing non-English books, journals and articles, the number of searches was reduced to 1279. Factors such as publication date, peer review status, and direct alignment with the research objectives of this paper were carefully considered. The titles and abstracts of the retrieved articles were rigorously reviewed to determine their consistency with the research objective. After a corresponding assessment by including and excluding relevant titles and abstracts, the total number of papers was further reduced to 563. Not only that, but the search papers must also meet the criteria for inclusion in the study, such as:

- i. The paper must be published in a peer-reviewed international journal or in the proceedings of an international conference in English. This practice facilitates the systematic acquisition of relevant information.
- ii. The topic must include at least one essential attribute related to the topic, such as the title, keywords, abstract, and body content mentioned previously.

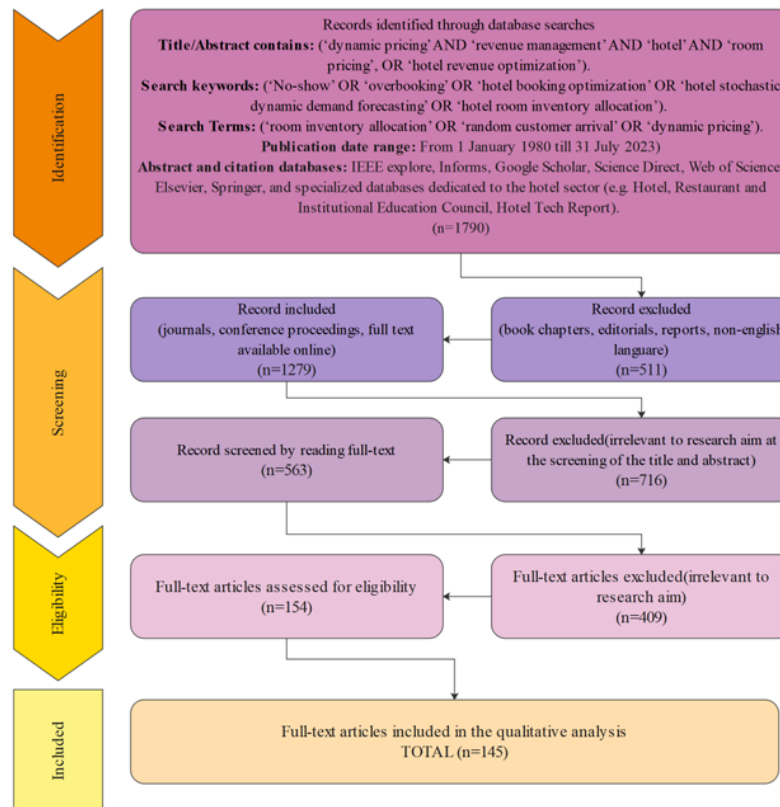


Fig. 1. PRISMA Four-phase Flow Diagram

The quality and credibility of the selected literature is rigorously assessed under the guidance of pre-determined criteria, making it possible to distinguish between high level research and unreliable sources. Finally, 409 papers were found not to be relevant to the study, including papers on customer ethics issues related to economics, price ethics, data privacy, customer experience and system development. After completing the final quality screening, another 9 papers were excluded. Consequently, these irrelevant papers were identified and eliminated, leading to a final selection of 145 papers for inclusion in the review. For the 145 papers included, we conducted a descriptive analysis based on the year of publication. The results show that there has been a consistent interest in the topic of HRRM from 1980 to 2025, as shown in Figure 2.

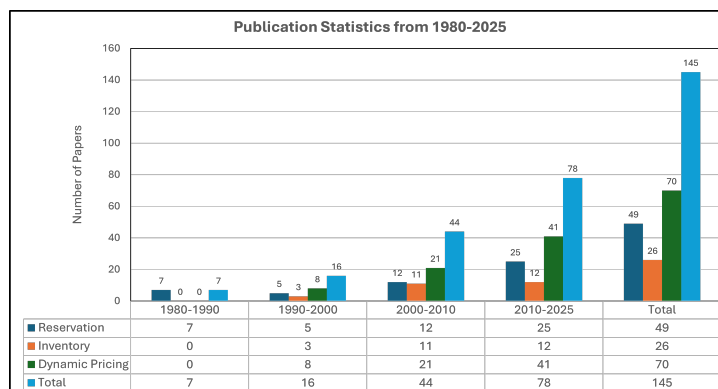


Fig. 2. Publication Statistics from 1980 to 2025

3.2 Classification of Problem Characteristics

The authors systematically classified 145 selected studies based on key problem characteristics. As summarized in Table 2, the problem characteristics in HRRM are organized into three main categories: reservation management, inventory allocation, and dynamic pricing [2]. Each characteristic is further subdivided into specific subcategories.

To ensure the rigor and transparency of the classification process, a structured coding procedure was adopted. First, all selected studies were independently reviewed and preliminarily categorized based on their primary research focus, as identified from their objectives, methodologies, and key contributions. The classification framework was iteratively refined to ensure conceptual clarity and consistency across categories. To enhance reliability, the classification was conducted by two reviewers. Discrepancies in categorization were discussed and resolved through consensus. In cases where a study addressed multiple problem characteristics, multiple classifications were allowed to reflect the interdisciplinary nature of HRRM research.

The reservation management category includes demand forecasting, customer arrival, and overbooking/no-show/cancellation. Inventory allocation covers multi-day capacity allocation, multi-product with fixed pricing, single product at multi-pricing, and multi-channel distribution. Finally, dynamic pricing comprises six subcategories, including capacity control, stochastic demand, time dependence, continuous time, competitive pricing, and third-party collaborations (i.e., OTAs).

Table 2
 Classification of Problem Characteristics in HRRM

Main categories	Sub-categories
Reservation Management	Demand forecasting
	Customer arrival
	Overbooking/No-show/Cancellation
Inventory Allocation	Multi-day capacity allocation
	Multi-product with fixed pricing
	Single product at multi-pricing
	Single product at multi-channels
Dynamic Pricing	Capacity control
	Stochastic demand
	Time dependence
	Continuous time
	Competitive pricing
	Third-party cooperation (OTAs)

4. Reviews of Problem Characteristics

4.1 Reservation Management

Reservation-related issues in HRRM encompass demand forecasting, customer arrival behavior, and overbooking/no-show/cancellations, which are central to optimizing booking operations and resource allocation [22, 23]. Thus, a significant direction in academic research has focused on two key research topics: (i) demand forecasting Ampountolas [24] and Phumchusri and Suwatanapongched [25] and (ii) optimization models [26-31]. Researchers predict future demand by analyzing historical data and current booking activity to set up a prediction module. Much of the existing literature focuses heavily on deterministic or historical-data-driven approaches, often overlooking real-time adaptability and the growing complexity of consumer behavior.

4.1.1 Demand Forecasting

Accurate demand forecasting is essential in HRRM for setting optimal prices and managing inventory. Early studies demonstrated the effectiveness of time-series models. For instance, Andrew *et al.*, [32] showed that both Box-Jenkins and exponential smoothing models provided high accuracy using data from a city hotel. Similarly, Weatherford and Kimes [33] compared multiple forecasting techniques and concluded that exponential smoothing, picking curves, and moving averages consistently outperformed booking-curve-based methods, which often yielded suboptimal accuracy [34-37].

In response to the limitations of deterministic approaches, stochastic and simulation-based models were developed. Fiori and Foroni [38] introduced a generalized linear model (GLM)-based stochastic framework that constructs demand prediction intervals, outperforming traditional time-series models in interval forecasting. El Gayar *et al.*, [39] proposed a Monte Carlo simulation approach that generated forecast densities and confidence intervals by modeling the entire reservation process. Their method offered advantages in estimating unconstrained demand, accounting for uncertainty beyond room capacity limitations, an aspect often neglected in earlier work.

Building on simulation and optimization, O'Neill *et al.*, [40] integrated nonlinear programming with Monte Carlo simulations to optimize pricing under stochastic consumer behavior, using price elasticity as a key input. Bandalouski *et al.*, [41] extended this further by incorporating demand segmentation and elastic demand simulation into a concave quadratic programming model. Their simulation experiments demonstrated revenue improvements of approximately 6% compared to fixed-price policies. Despite these advances, several gaps remain. Many models rely on historical data under the assumption of stationarity, limiting their robustness in volatile environments (e.g., post-COVID recovery periods or demand shocks). Furthermore, while simulation models provide greater flexibility, they are often computationally intensive and rarely adopted by small and mid-sized hotels who lack technical expertise. Additionally, few forecasting models are evaluated using standardized benchmarks, making cross-study comparisons difficult.

4.1.2 Customer Arrival

Customer arrivals in hotels are broadly classified into two categories: advance bookings and uncertain (walk-in or last-minute) arrivals [42]. Advance booking models received substantial attention, with studies leveraging historical booking curves and regression analysis to predict final occupancy levels. For instance, Tse *et al.*, [43] modeled booking trends using a quadratic function over a 90-day window, achieving high predictive accuracy for Hotel ICON in Hong Kong. Similar approaches were adopted using autoregressive models and machine learning (ML) techniques to refine short-term forecasts and fit booking behavior trends [44-47]. However, these models often assume consistent customer behavior and may struggle with structural shifts in booking patterns driven by external factors such as price fluctuations, seasonality, or promotional campaigns. Additionally, few studies incorporate real-time updates or adaptive mechanisms to improve forecast responsiveness. In contrast, modeling uncertain or random arrivals presents greater complexity due to their stochastic nature. Bitran and Gilbert [48] introduced a heuristic acceptance policy combined with stochastic dynamic programming to manage room allocations under uncertain demand. Lai and Ng [49] adopted robust optimization methods to handle unpredictability in arrival timing and guest length of stay, offering improved resilience in volatile scenarios.

Ampountolas [50] employed vector autoregression (VAR) and vector error correction models to estimate demand uncertainty, providing a probabilistic forecast framework. Similarly, Holt-Winters smoothing has been used to combine long-term demand trends with short-term booking activity, allowing for adaptive weighting based on forecast error metrics [51, 52]. Weatherford and Kimes [33] further proposed heuristic decision models for perishable hotel assets, integrating both advance and walk-in arrivals through a transfer pricing model that optimizes over two customer segments.

While effective in theory, such models often rely on simplifying assumptions and may not fully capture the dynamic interactions between pricing, availability, and arrival behavior. Despite the variety of approaches, the literature remains fragmented, with limited efforts to unify arrival modeling into a comprehensive, real-time, and adaptive decision support system. Most models focus either on deterministic patterns or assume full knowledge of distributional parameters, which is often unrealistic in practice. There is a pressing need for integrated frameworks that can simultaneously accommodate advance and stochastic arrivals, adapt to new data, and support pricing and allocation decisions in real time.

4.1.3 Overbooking/No-show/Cancellation

Overbooking arises when hotels accept more reservations than available rooms, anticipating no-shows, cancellations, or early departures. While this strategy can mitigate revenue loss from unused capacity, it carries reputational and operational risks when actual cancellations fall below expectations. To address this, numerous studies proposed predictive models and simulation-based policies for optimal overbooking levels [53-58]. Early works, such as Corney [59] employed basic spreadsheet-based models to determine optimal overbooking levels, emphasizing computational efficiency. Toh [60] introduced a capacity-depletion model that classified guests into types (e.g., stayovers, walk-ins) using empirical data from multiple hotels. While practical, these early models are limited by their reliance on static assumptions and do not account for dynamic market conditions.

More advanced studies integrated inventory control with overbooking optimization. For example, Baker and Collier [61] compared heuristic methods such as Threshold Curve Method (TCM), Nested Deterministic Shadow Pricing (NDSP), and Hotel Bid Price Method (HBPM), concluding that heuristic-based bidding strategies perform well in high-demand, high-volatility settings. However, these approaches often ignore interdependencies between customer behavior, price sensitivity, and booking channels.

Stochastic models were also explored. Koide and Ishii [62] applied a Markov framework for pricing and overbooking, albeit under simplified assumptions excluding no-shows. Later models, such as those by Phumchusri and Suwatanapongched [25] and Vajpai and Ramnagar [63] incorporated random cancellations and used Poisson distributions to estimate future arrivals. While statistically rigorous, many of these studies fail to capture real-world variance and the economic cost of customer displacement due to overbooking errors.

Big data applications also provide new insights. Morales and Wang [64] used name-based booking records to develop a time-dependent cancellation model, highlighting the need to coordinate prediction across temporal windows. Similarly, Sierag [65] identified significant variations in cancellation and arrival behavior across time-of-day and customer segments, emphasizing the importance of granular modeling. However, despite these contributions, many ML-based models still lack transparency, making it difficult to operate in decision support systems.

Recent research has leveraged ML to improve prediction accuracy. Gibbs *et al.*, [66] built ML models based on data from four hotels, demonstrating that performance improves when models are tailored to property-specific features. In a follow-up study, António [67] incorporated diverse data

types, e.g., weather, events, pricing trends, into a unified ML framework, yielding high cancellation prediction accuracy. Despite these advancements, interpretability and integration with real-time RM systems remain challenging. Gao [68] employed multiple ML models to predict customer booking cancellations. The research findings indicated that eXtreme Gradient Boosting (XGBoost) outperformed all other models, with a predictive performance of approximately 0.79. Among them, deposit type and market segmentation were identified as key factors influencing booking cancellations.

Ampountolas [69] also employed ML methods to predict booking cancellations. However, sensitivity tests were introduced based on model comparisons to verify the reliability of the predictions. The results showed that the K-Nearest Neighbors (KNN) and XGBoost-ridge regression hybrid model performed exceptionally well in terms of recall rate, effectively reducing the false negative rate, and thereby enhancing the reliability of the cancellation predictions. Ampountolas and Legg [70] proposed an ML model that considers time trends and predicts reservation cancellations by introducing time lag variables. The research results show that, over a longer time span, the artificial neural network multi-layer perception (ANN-MLP) outperforms other ML models in terms of prediction performance.

Overall, while literature offers a wide range of approaches, from heuristic and statistical models to advanced ML, many suffer from limited generalizability, oversimplified assumptions, or insufficient attention to DP interactions. Few models integrate overbooking decisions with personalized pricing, channel management, or ethical considerations such as customer dissatisfaction. There remains a significant gap in developing robust, interpretable, and real-time adaptable overbooking models tailored to diverse hotel settings.

4.2 Inventory Allocation

Inventory allocation in the hotel industry refers to the strategic distribution and management of available room inventory across various booking channels to maximize revenue and occupancy rates [71]. This process is integral to RM and involves careful planning and forecasting to ensure that rooms are sold at the optimal price, while minimizing the risk of unsold inventory [72]. Frequently, capacity allocation and controls are integrated with customer demand prediction and dynamic pricing [73, 74]. The creation of a prevalent method for matching supply and demand is widely employed in RM for perishable goods like airline seats, hotel rooms, and car rental services [75-77]. Emerging as a novel model within HRRM systems, the incorporation of capacity control with demand prediction offers hotel managers a more effective tool. By selling hotel rooms to various customer categories at distinct price points, this strategy attains an optimal revenue level, as demonstrated by the work of Cho *et al.*, [78].

4.2.1 Multi-day Capacity Allocation

Managing multi-day guest stays presents a complex challenge in hotel room allocation, as it requires simultaneously optimizing current occupancy and future booking opportunities. Early work by Weatherford [79] introduced a Poisson-based heuristic that incorporated length-of-stay (LOS) into demand modelling. Their approach improved prediction accuracy by 2.94% compared to standard revenue rules that ignored LOS considerations.

Subsequent studies explored integrated frameworks combining overbooking and room allocation. Cezar and Ögüt [80] proposed hotel-specific algorithms that jointly manage booking limits and room assignments. Baker *et al.*, [81] extended the work with a predictive allocation model that

explicitly links time-based demand forecasting with inventory constraints. Choi [82] further emphasized channel-specific booking costs, highlighting the value of incorporating distribution-level decisions into room allocation strategies.

Aydin and Birbill [83] introduced a decomposition-based allocation model, distinguishing between day-based (pre-booked) and period-based (in-house guests) assignments. Their linear programming model provided optimal allocation strategies but assumed full information and excluded walk-ins or uncertain arrivals, limiting its robustness in real-world operations [84]. A novel contribution was made by Battiti *et al.*, [85] who developed RoomTetris, a heuristic optimization algorithm that assigns specific room numbers rather than just room types. By simulating guest behavior and booking scenarios, the model strategically prioritizes longer stays over shorter ones to preserve future capacity, leading to improved occupancy and revenue. This study bridged statistical modeling with combinatorial optimization, presenting the “room commitment problem” as an emerging subfield in intelligent room allocation.

While these studies mark significant progress, several limitations persist. Most models assume deterministic demand or ignore last-minute bookings and cancellations. Few frameworks adapt in real time or incorporate dynamic pricing as a constraint within the allocation logic. Moreover, the trade-off between maximizing occupancy and maintaining guest satisfaction, particularly when reassigning rooms or declining short stay remains underexplored.

4.2.2 Multi-products at Deterministic

Price Inventory allocation for multiple room types at fixed prices is a common strategy in hotel RM. Kuyumcu and Popescu [86] simplified the multi-product inventory problem into a nonlinear programming model with concave objectives and linear constraints, achieving practical applicability in large hotel chains. Subsequent studies extended this approach using linear demand models for deterministic control [87, 88].

Qin [89] applied a multinomial logit model to estimate consumer choice probabilities across different room types, leveraging historical data to optimize room-type allocation. Similarly, Pimentel *et al.*, [90] incorporated a price-sensitivity model in their optimization algorithm, using bid pricing strategies to improve allocation performance. However, the study excluded group bookings and temporal dynamics, limiting its generalizability. Zilan *et al.*, [91] framed room allocation as a probabilistic estimation problem and compared classical statistical methods with data-driven optimization. Their results favored data-driven approaches for greater numerical accuracy, but scalability and interpretability under operational constraints remain underexplored.

4.2.3 Single Product at Multi-prices

Dynamic pricing strategies for a single room type aim to extract maximum willingness-to-pay from different customer segments [92, 93]. This form of price discrimination adjusts room rates based on booking lead time, demand, and customer type [94].

Wang *et al.*, [95] constructed a system integrating demand forecasting, allocation optimization, and final allocation, transforming a stochastic model into a tractable linear program via robust optimization. While useful in structured scenarios, its reliance on static demand assumptions limits adaptability. Ni *et al.*, [96] addressed the allocation problem from a max–min regret perspective under risk-neutral assumptions, modeling early-arriving, low-price customers versus late-arriving, high-price customers. However, the model does not account for demand uncertainty, cancellations, or overbooking, which are prevalent in practice. Zhuang *et al.*, [97] developed a stochastic dynamic

model integrating capacity control and dynamic pricing under non-advanced demand information (ADI). Their policy used multi-threshold strategies based on system states, and results showed significant revenue enhancement, up to 58% price spread, though real-time implementation remains challenging due to data and computational complexity.

4.2.4 Single Product at Multi-channels

Selling the same product across multiple distribution channels, e.g., hotel websites, OTAs, and travel agencies, enhances visibility and revenue diversification [98, 99]. Effective channel management requires balancing commission costs, price parity, and customer reach. Nakano *et al.*, [100] modeled the inventory allocation problem across channels using dynamic programming and simulations, assuming known demand distributions and single room types. While methodologically sound, the model's assumptions may not hold in real-world settings where customer behavior is less predictable. More recently, Liu *et al.*, [101] employed historical data and a heuristic greedy algorithm to allocate rooms among online distribution channels under random arrival patterns. Although the model offered practical insights, its simplicity may restrict performance in highly dynamic or high-volume environments.

4.3 Dynamic Pricing

Dynamic pricing (DP) refers to a RM approach in which hotel room rates are continuously adjusted in real time in response to fluctuations in market demand, reservation patterns, competitors pricing, and external factors such as special events [102]. Leveraging advanced algorithms and data-driven systems, hotels dynamically modify prices to maintain competitiveness and maximize revenue. Prior research has underscored the strategic value of DP in hospitality. Choi and Cho [103] highlighted that responsive pricing aligned with demand fluctuations enables hotels to achieve optimal revenue outcomes. Gao [68] employed multiple linear regression to conduct an empirical analysis of the key control variables in hotel pricing strategies. The research findings indicated that hotel type, customer evaluation level, and geographical location play a decisive role in the formation of room prices. Suresh *et al.*, [104] focused on the dynamic pricing mechanism and exploring the application of information computing in price decision-making and market response. It points out that by continuously analyzing large-scale data, assessing the competitive environment, and predicting demand fluctuations, enterprises can achieve more adaptive pricing strategies and revenue optimization in a highly automated and rapidly changing business environment.

4.3.1 Capacity Control

Capacity control is a core component of hotel RM, involving strategic allocation of room inventory across price categories to maximize revenue based on fluctuating supply and demand [105]. This practice is often integrated with DP, customer segmentation, and promotional strategies to form a comprehensive revenue optimization framework [106-112]. Maglaras and Meissner [113] proposed heuristic algorithms for multi-product capacity control under resource constraints. Their "fluid" model, which replaces discrete stochastic demand with continuous approximations, proved asymptotically optimal for large-scale problems. Numerical experiments demonstrated that these heuristics outperform deterministic models, especially in scenarios of capacity scarcity.

Recent advancements applied reinforcement learning (RL) to DP and capacity control. Singh [114] implemented a deep Q-network agent trained on real hotel data, showing revenue improvements of

15–20% over traditional fixed pricing. Tuncay *et al.*, [115] applied Q-learning within a Markov Decision Process framework, incorporating profit- and demand-based reward functions. Their model integrates pricing with promotional responses to dynamically manage occupancy and profitability. While promising, RL-based approaches face challenges such as high data requirements, interpretability, and computational costs. Moreover, most studies assume perfect information and homogeneous room types, limiting real-world scalability. Future research should explore hybrid models combining heuristic rules with RL to enhance both performance and practical implementation.

4.3.2 Stochastic Demand

Stochastic demand refers to demand patterns influenced by inherent uncertainty and randomness, often driven by factors such as weather, local events, and macroeconomic fluctuations [116, 117]. In hotel RM, accurately modelling stochastic demand is essential for implementing responsive DP strategies that optimize both revenue and occupancy rates [118]. Numerous studies developed models that incorporate demand uncertainty into DP frameworks. Among these, elastic demand models are widely used to quantify the impact of price on customer booking decisions and to adjust prices in real time [119, 120].

Zhao and Zheng [121] demonstrated that under stochastic arrivals and fixed inventory, optimal prices decline over time. Their DP policy improved revenue by 2.4–7.3% compared to static pricing. Aziz *et al.*, [122] applied nonlinear programming and simulation to model historical demand and estimate price elasticity, yielding optimized nightly pricing over fixed price tiers. Other research integrates stochastic demand into operational systems. Vives and Jacob [123] developed a hybrid deterministic-stochastic pricing model applied to resort hotels, while Hanwu and Peng [84] combined heuristic and stochastic methods to enhance pricing accuracy. In Indonesia, Fadly *et al.*, [124] modeled non-linear demand-price relationships across room types, reporting a 27% revenue increase over static pricing approaches.

Zhu *et al.*, [125] proposed a multi-task dynamic pricing framework that integrates price elasticity learning and demand prediction. Their model leveraged competition-aware modules and multi-series data fusion to address data sparsity and improve pricing precision. The framework demonstrated superior performance in forecasting and real-time pricing, offering practical applicability in online hotel booking platforms. Despite these advancements, challenges persist. Many models require accurate estimation of demand distributions, which is often infeasible in volatile environments. Additionally, the integration of stochastic demand with other RM components such as overbooking or channel management remains limited. Future research should focus on real-time, adaptive systems that incorporate multi-source data and balance predictive accuracy with computational efficiency.

4.3.3 Time-Dependent

Time-dependent pricing strategies are fundamental in hotel RM, as room demand fluctuates significantly across temporal segments such as weekdays, weekends, peak seasons, and special events [15]. By segmenting time into multiple intervals, hotels can adjust room rates dynamically to align supply with expected demand. While multi-period strategies allow for granular control and responsiveness, single-period models are simpler and suitable when demand is concentrated or predictable, such as during major events [123].

Time-sensitive pricing also includes temporal proximity-based adjustments, prices typically rise closer to high-demand dates to encourage early bookings or drop nearer to check-in dates to reduce unsold inventory [119]. This dynamic adaptation allows hotels to exploit temporal value shifts in perishable inventory. Hong *et al.*, [126] modeled multi-product pricing over multiple time periods using a non-parametric online stochastic optimization framework. Their approach, based on a Kiefer–Wolfowitz approximation, performed comparably to traditional parametric methods and proved effective in handling dimensional complexity in high-dimensional pricing problems.

Wang *et al.*, [127] addressed single-product pricing in limited time using a dynamic learning-while-doing algorithm. Their model achieved optimal regret bounds and allowed real-time price adaptation based on demand feedback, highlighting the trade-off between exploration and exploitation in short booking windows. Vives and Jacob [123] implemented a deterministic-stochastic hybrid model to identify optimal time-based pricing strategies in resort hotels, incorporating booking duration and demand elasticity. However, the study acknowledged limitations related to the exclusion of competitor pricing and segment-specific behaviors.

Akçay *et al.*, [128] developed a joint pricing model for multiple perishable products sold within a fixed horizon. Their stochastic dynamic programming formulation captured consumer utility across vertically and horizontally differentiated products and provided polynomial-time solutions for optimal pricing paths. Meschede *et al.*, [129] applied renewable energy systems for island hotels are highly sensitive to weather and occupancy fluctuations, with electricity demand dominating costs and an optimal renewable mix improving both efficiency and risk assessment. Similarly, Lin and Sibdari [130] introduced a time-dependent “switching strategy” using a random knapsack model and convex programming to determine optimal price transitions based on real-time demand.

While time-dependent models are well-established, many rely on idealized assumptions such as known demand functions or fixed seasonality. In practice, forecasting accuracy is often limited by external volatility and data sparsity. Future models must better integrate competitor actions, multi-channel behavior, and non-stationary demand signals to fully realize the benefits of temporal price optimization.

4.3.4 Continuous Time

Continuous-time models treat time as fluid, allowing price and inventory decisions to adjust at any moment. These models typically employ differential equations or optimal control theory to address DP problems with high temporal granularity [131]. In contrast to continuous-time approaches, discrete-time models operate in fixed intervals (e.g., daily), offering greater compatibility with hotel pricing systems that typically adjust rates at regular time steps [132, 133]. Despite their theoretical accuracy, continuous-time models are rarely used in practice due to complexity and data requirements [134].

Feng and Xiao [135] proposed a reversible pricing model using intensity control and closed-form solutions under a continuous framework. Levin *et al.*, [136] applied continuous-time control to integrate risk measures into DP, providing a mechanism to reduce variance in earnings. Meanwhile, Levin *et al.*, [137] addressed price guarantees using discrete-time Markov models and nonlinear programming, bridging the theoretical-practical divide with approximation techniques. Although continuous-time models offer finer control, they remain limited in real-world applications due to computational burden and limited system compatibility. Most hotel RM systems still rely on discrete frameworks due to operational feasibility and integration ease.

4.3.5 Competitive Pricing

Competitive pricing refers to the strategic adjustment of rates based on real-time monitoring and analysis of competitors' offerings within the same market [138, 139]. Hotels typically collect competitor pricing through OTAs and rate intelligence tools, updating their own rates to maintain market positioning while optimizing revenue [140].

In this context, game theory has been widely used to analyze price competition. Dai *et al.*, [141] modeled Nash equilibrium pricing strategies under deterministic and stochastic demand. Lin and Sibdari [142] used multinomial logit models in a heuristic game-theoretic framework, showing that customer choice depends not only on a hotel's price but also on that of its competitors. Bai and Tang [143] explored how transient demand forecasts influence optimal pricing against rival bids. Armillotta [144] used OTA-derived data to build a network autoregressive model of competitive behavior in Venice hotels, revealing dynamic interdependencies in pricing decisions across time, room type, and lead time. Based on the FairPlay cooperative game pricing framework, Mohammadzadeh Abachi *et al.*, [145] introduced the modeling of regional and competitive relationships based on graph node embedding, to depict the spatial agglomeration and local competitive effects among hotels, thereby achieving a fairer, more dynamic and market-adaptive hotel pricing mechanism. While competitive pricing models offer strong theoretical insights, their operational translation is often hindered by assumptions of complete information and rational behavior. Real-world RM must contend with incomplete data, heterogeneous competitors, and consumer irrationality, which many models fail to address.

4.3.6 Third-party Cooperation (OTAs)

Online travel agencies (OTAs) such as Booking®, Expedia®, and Agoda® play a pivotal role in hotel RM by broadening market access, facilitating DP strategies, and offering real-time insights into customer demand [146]. OTAs allow hotels to flexibly adjust room rates in response to market demand, inventory levels, and competitor pricing [147]. However, effective cooperation requires alignment with direct booking strategies to prevent revenue dilution from high commission costs.

Maglaras and Meissner [113] examined optimal pricing in OTA-hotel partnerships using a non-cooperative Nash game framework under the assumption of hotel homogeneity. Their model demonstrated how decentralized decision-making among hotels influences overall pricing strategies. Similar game-theoretic approaches were examined in studies by [134, 148-151]. Ling *et al.*, [149] further proposed managing OTA availability dynamically by withholding inventory close to check-in dates. This approach aimed to reduce OTA commissions by encouraging direct bookings, while still leveraging OTAs for demand generation.

Aygün and Bulut [151] introduced a two-stage optimization model combining overbooking and OTA cooperation. Using a leader–follower Nash game solved via genetic algorithms, they found that hotel operational efforts, capacity, and length of stay influence profit-sharing between hotels and OTAs. Interestingly, greater efforts improved hotel profits but reduced OTA margins, highlighting the complex interdependence in third-party partnerships. Guizzardi *et al.*, [134] applied nonlinear time series and reverse-engineering techniques to analyze price adjustments of Milanese hotels on OTA platforms. They observed that price-setting behaviors exhibit temporal autocorrelation and are influenced by hotel characteristics such as size and brand. Their point-based simulation method revealed how early pricing decisions shape last-minute adjustments in response to fluctuating demand. While OTAs offer increased visibility and revenue potential, their integration with hotel RM systems poses challenges. These include commission costs, loss of pricing control, and potential

cannibalization of direct sales. Future work should focus on hybrid pricing strategies that dynamically balance OTA exposure with direct booking incentives to achieve long-term revenue optimization.

5. Overall Observations

The body of research in HRRM is primarily categorized into three focal areas: reservation management, inventory allocation, and dynamic pricing. Among these, dynamic pricing has garnered the most scholarly attention, followed by reservation management and inventory allocation.

Research in reservation management predominantly emphasizes demand forecasting, leveraging mathematical models, heuristic algorithms, and increasingly, machine learning methods. Key challenges such as overbooking, no-shows, and unknown arrivals attracted sustained focus, with many studies adopting pairwise coupling strategies (e.g., overbooking with cancellation) to simplify problem complexity and enhance tractability. However, despite notable advances, several limitations remain. Many forecasting models rely on historical data under stationarity assumptions, rendering them less robust in volatile contexts such as post-COVID recovery or during demand shocks. Furthermore, while simulation-based models offer flexibility, they are often computationally intensive and seldom implemented by small or mid-sized hotels due to technological and expertise barrier.

Additionally, few studies employ standardized evaluation benchmarks, hindering model comparison and generalization. Arrival modelling remains largely fragmented, with limited efforts to establish integrated, real-time, and adaptive decision support systems that can jointly handle both advance and stochastic arrivals. The dominant use of deterministic demand patterns or fully specified distributional assumptions limits practical applicability in real-world settings characterized by uncertainty and incomplete information.

Inventory allocation research largely addresses the control of multi-day bookings, multi-product offerings, and room-type management. Although frequently embedded within broader pricing or forecasting frameworks, few studies isolate inventory allocation as an independent optimization problem. Most models rely on heuristic or mathematical programming approaches, often assuming known demand functions and deterministic conditions. Real-time adaptability and integration with dynamic pricing mechanisms remain underexplored.

Furthermore, most allocation models neglect last-minute cancellations and booking adjustments, which are prevalent in hotel operations. Very few frameworks incorporate dynamic pricing as a constraint within allocation decisions, and fewer still address trade-offs between occupancy maximization and guest satisfaction, especially in scenarios involving short-stay rejections or room reassignment. There is a critical gap in the development of interpretable, real-time, and context-aware inventory allocation strategies, particularly those suited to heterogeneous hotel environments.

Dynamic pricing has evolved into the most intensively studied area in HRRM, driven by advances in data analytics and algorithmic optimization. Scholars proposed a wide array of models, from heuristic and rule-based approaches to machine learning and reinforcement learning to align pricing with demand fluctuations, competitive activity, and customer segmentation. From 2010 to 2025, a clear trend emerged toward forecasting-integrated dynamic pricing frameworks, particularly those incorporating AI and predictive analytics.

Nevertheless, the field faces several pressing challenges. Many models assume perfect market knowledge, homogeneous room types, and stable seasonal patterns, assumptions that are rarely held in practice. Time-dependent models, though theoretically sound, often oversimplify demand fluctuations by ignoring competitor dynamics, multi-channel interactions, and non-stationary data

signals. Additionally, while continuous-time pricing models allow finer granularity, they are seldom deployed in practice due to high computational costs and low system compatibility; most real-world systems continue to rely on discrete-time models for ease of implementation.

Reinforcement learning-based methods have shown potential but require large datasets, complex tuning, and lack interpretability, limiting their feasibility in most hotel settings. Hybrid models that combine reinforcement learning with heuristic decision rules offer a promising direction for balancing accuracy and operational applicability. Moreover, stochastic demand modeling, though rich in theoretical depth, remains difficult to implement due to the need for accurate distributional estimations, which are often infeasible in fast-changing markets.

Across all areas, a significant research gap lies in the lack of unified frameworks that jointly optimize overbooking, pricing, and channel management. Most models treat these components independently, ignoring their interdependence and compounding effects. Few studies consider personalized pricing, ethical concerns, or customer dissatisfaction in overbooking decisions. Despite the use of sophisticated optimization models, generalizability and real-time adaptability remain limited, especially under sparsity and noisy environments.

The rise of OTAs has further complicated RM strategies. While OTAs offer broader visibility and access to diverse customer segments, they introduce challenges such as commission costs, pricing dilution, and direct booking cannibalization. Many studies had not fully integrated OTA cooperation mechanisms into dynamic pricing or inventory control frameworks. Emerging research highlights the need for hybrid pricing strategies that can balance OTA exposure with direct booking incentives in a dynamic and revenue-maximizing manner.

6. Challenges and Future Work

6.1 Reservation Management

For a long time, dynamic demand fluctuations, market uncertainties, and the complexity of distribution channels were the main challenges in the field of hotel revenue management. Prediction models largely rely on the quality of historical data in hotel management systems for their training data. With the increasing concern for data privacy, developing models that can provide accurate predictions without infringing on individual privacy rights poses a challenge. Adapting models to data distribution over time and continuous learning is a significant challenge. Instant capture and real-time decision-making are particularly important in the uncertain environment of hotel revenue management, as potential factors and patterns are constantly changing.

An analysis of the screened literature indicates that deep learning techniques, especially neural networks, achieved remarkable success in various prediction tasks. Deep learning models, such as convolutional neural networks and recurrent neural networks, performed well in image recognition, natural language processing, and time series prediction. Transfer learning is becoming increasingly popular, allowing models pre-trained on one task to be fine-tuned for another related task. This approach has proven effective when labeled data is limited. Ensemble methods, which combined the predictions of multiple models, were widely studied and adopted. Techniques such as random forests, gradient boosting, and stacking help improve model robustness and accuracy.

Looking ahead to the efforts to overcome these challenges, several key approaches emerge:

- i. Algorithms for predicting seasonality and special events need to be more responsive and accurate. Better identification of sudden events such as large-scale activities and seasonal changes can facilitate dynamic price adjustments that are not lagging, allowing for accurate and timely predictions and responses.

- ii. Advanced algorithms and ML should be utilized to optimize inventory and control revenue losses caused by overbooking, no-shows, and cancellations.
- iii. Future predictions will no longer be a single number from a single model, but rather a fusion of AI, ML, and real-time data, with models continuously updated and corrected, enabling hotel managers to truly understand what is happening in the market and make more accurate and timely decisions.

6.2 Inventory Allocation

To enhance the utilization rate of hotel room resources, hotels usually adopt overbooking strategies to cope with the perishability of room inventory. However, due to the unpredictability of cancellation of reservations and unoccupied rooms, overbooking may result in service non-fulfilment or potential revenue loss. The unpredictability of customer arrivals makes real-time management of distribution inventory across multiple online and offline channels increasingly complex, and improper allocation or unreasonable pricing may reduce customer satisfaction due to inconsistent room supply.

The literature indicates data integration and algorithmic decision support systems can significantly improve prediction accuracy and reduce the risk of overbooking. Advances in computational mathematics and high-performance computing drove the development of more realistic and efficient models, thereby promoting dynamic inventory management. Heuristic methods, especially hybrid and adaptive variants, demonstrate great potential in solving large-scale, dynamic pricing and inventory problems. Reinforcement learning has been introduced to improve heuristic decisions, while parallel and distributed models enhance the scalability of inventory management. However, these methods still face challenges such as lack of optimality guarantees, sensitivity to parameter adjustments, and insufficient adaptability in random and uncertainty environments.

Future research directions include developing integrated models that combine dynamic pricing with real-time inventory control for different customer groups and booking periods. Emphasis should be placed on leveraging machine learning-enhanced synchronous algorithms, intelligent distribution systems oriented towards channel performance and cost-effectiveness, and exploring blockchain technology for secure, decentralized inventory allocation.

6.3 Dynamic Pricing

Dynamic pricing strategies are highly dependent on accurate and timely data. Inconsistencies or incompleteness of data may lead to suboptimal pricing decisions. Additionally, devising the optimal pricing strategy by considering the behavior of competitors and market dynamics is a complex task. Implementing personalized pricing strategies, as well as promotional activities targeted at individual customers or specific market segments, and real-time monitoring of competitors' pricing strategies and making appropriate responses is a complex and highly challenging task.

The stochastic dynamic model is used to analyze the dynamic behavior of the system under constant changes and the influence of random variables. From relevant literature, scholars made significant progress in combining stochastic process theory with Monte Carlo simulation applications. This includes more accurate modeling of the dynamic behavior of stochastic systems and conducting large-scale random experiments using the Monte Carlo method. Machine learning methods also made certain progress in handling stochastic dynamic systems. This includes processing time series

data and uncertainties, thereby improving the adaptability of the model to complex dynamic systems.

Stochastic dynamic systems require high-quality data and precise uncertainty assessment. Correct modeling of uncertainty is crucial for the effectiveness of the model. To address these challenges, the following future work is proposed: improving the accuracy of data by seamlessly integrating various data sources to establish robust data quality control measures. Improving the accuracy of predictive analysis models enables hotels to actively optimize room supply and refine pricing strategies. Deploying advanced customer segmentation technologies (such as natural language processing, machine learning) through strict data analysis to understand individual customer preferences, thereby promoting the implementation of personalized pricing and promotional activities. Integrating customer relationship management systems with marketing systems to enhance understanding of customers, thereby achieving more effective personalized and targeted promotional activities. Making full use of the capabilities of artificial intelligence and machine learning to analyze customer behavior, predict their preferences, and dynamically adjust prices and promotional strategies in real time.

7. Conclusion

This systematic review applied the PRISMA framework to analyze 145 studies on HRRM over the past 45 years and classified the problem into three main issues: reservation management, inventory allocation, and dynamic pricing. Among these problem characteristics, reservation management and dynamic pricing had been the primary focus of researchers. Most of the literature combined classical forecasting models with optimization models, but relatively few independent studies addressed inventory allocation.

Since 2010, problem research models showed a trend of innovation and diversification, in which machine learning combined with mathematical models became a widely adopted approach by scholars. By adjusting parameter variables for mathematical modelling and solving, scholars tried to find optimal solutions to the problems. Topological methods and stochastic dynamics remained challenging in the modelling process. Researchers studying HRRM mainly used real hotel data, but those models were typically valid only for a single hotel in a specific study. There was no unified standard that could be integrated into a standard RM framework. In short, modelling was extremely data-intensive, and there was a lack of consistency in data and variable characteristics across hotels.

In terms of solution methods, the authors found that the most common approaches in HRRM were mathematical models combined with predictive models, mathematical models combined with dynamic optimization models, and heuristic methods. However, many research methods were used to improve prediction, such as deep learning and natural language processing. Researchers conducted large-scale randomized experiments with Monte Carlo simulations and Nash equilibrium analyses. Deep learning techniques showed increasing potential in modeling complex nonlinear and stochastic dynamics in revenue management contexts.

Ultimately, the field of HRRM was constantly changing and underwent evolution and innovation as technology and markets evolved. In-depth analysis of data, accurate prediction of dynamic environmental variables, and optimization of mathematical models combined with flexible decision making were critical to successfully implementing RM strategies. Researchers paid special attention to accurately modelling and obtaining optimal solutions in dynamic environments of uncertainty. Although the research literature on HRRM grew, the field was still not fully explored, and many new challenges and promising applications emerged. Therefore, this created a more exciting research environment for HRRM research.

This review, despite aiming for a comprehensive and structured overview of HRRM research, had several limitations. First, publication bias was possible because studies with significant or positive results were more likely to appear in indexed journals, which could skew the evidence base. Second, we restricted our search mainly to English-language publications, so important research published in other languages could have been omitted. Third, although we searched several major academic databases, coverage was not exhaustive; relevant industry reports and conference papers may have been missed. Finally, study selection, categorization, and thematic synthesis required researcher judgment; even with predefined inclusion criteria and a structured coding process, some subjectivity may have influenced interpretations. Readers should have interpreted our findings with these caveats in mind. Future work could have improved robustness by including multilingual sources, widening database coverage, and applying more standardized classification methods.

Based on the reviewed literature, several critical research gaps were identified: First, the integration of predictive models with optimization frameworks remained limited, particularly under real-time and data-driven decision environments. Second, existing studies often overlooked data imbalance and decision-relevant rare events, which were crucial in practical RM scenarios. Third, the incorporation of unstructured data (e.g., customer reviews and sentiment) into optimization-oriented models was still underexplored. Finally, there was a lack of robust multi-objective frameworks that simultaneously considered profit, demand uncertainty, and pricing stability.

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Conflict of Interest Statement

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Author Contributions Statement

Tian TIAN conceptualized and designed the study, conducted the experiments and data analysis, and wrote the original draft of the manuscript. Aneng HE contributed to data interpretation and assisted with the methodology and analysis. Lai Soon LEE supervised the project, provided research guidance, and reviewed and edited the manuscript. All authors contributed to manuscript revision, read, and approved the final version of the manuscript.

Data Availability Statement

All data generated or analysed during this study are included in this published article. Additional datasets are available from the corresponding author upon reasonable request. Where applicable, publicly available datasets used in the study are cited in the references.

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